

Research Article

A Novel Scheduling Algorithm Based on Game Theory and Multicriteria Decision Making in LTE Network

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Received 27 July 2014; Revised 18 December 2014; Accepted 19 December 2014

Academic Editor: Lillykutty Jacob

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Fourth generation wireless networks provide mobile users with high data rate and quality of services, such as Long Term Evolution (LTE), which has been developed by the 3rd Generation Partnership Project (3GPP). However, 3GPP is not a standardized scheduling algorithm to utilize LTE properties in smart grid applications. This paper proposes a two-level scheduling scheme composed of cooperative game theory (bankruptcy and shapely) and Technique for Order Performance by Similarity to Ideal Solution (TOPSIS). The proposed algorithm improves resource allocation for three smart grid applications, namely, voice, video surveillance, and metering data. On the first level, bankruptcy and shapely value algorithm fairly distribute the resources among smart grid applications. On the second level, TOPSIS algorithm allocates the resources among application's users based on their criteria and the application's preferences. Moreover, the system's performance has been evaluated in terms of throughput, delay, and fairness index. The proposed algorithm is compared with existing algorithms, such as proportional fairness, modified largest weighted delay first, and exponential rule schemes. The results show a significant improvement compared to other algorithms. This paper presents a novel technique consisting of both TOPSIS and game theory algorithms to study three smart grid applications. The novel algorithm has proven to be an effective scheduling technique for smart grid applications.

1. Introduction

Nowadays, smart grid has drawn a lot of research interests due to its ability to provide valuable information to monitor, control, and manage source generation, substation, and consumers' power consumption. Some of the key smart grid components are advance meter infrastructures (AMI) and phasor measure units (PMU) [1, 2]. Moreover, AMI provides consumers with full information on the electricity status, such as consumption rates, and then the data is transmitted to the control centre through a communications network. PMU also has an essential role since it provides monitoring for voltage and current. Furthermore, it is fixed at the power generator and the substation. For real monitoring, the smart grid utilizes smart applications, such as video surveillance and voice (work force).

According to [3], LTE is a promising technology for smart grid applications since it demonstrates a good performance

in terms of delay, data rate, and reliability compared to other technologies. In addition, the LTE system represents an important milestone towards the so called 4G cellular networks. However, LTE is not a standardized scheduling algorithm for smart grid applications despite the fact that it plays a crucial role in the smart grid performance. The scheduling mechanism handles the resource distribution among the users. To be more precise, it chooses how to distribute radio resources among different stations taking into account channel condition and quality of service (QoS) requirements. Moreover, scheduling process is handled by the base station at the medium access control (MAC) layer for LTE network [4]. Uplink and downlink scheduling are separated in LTE and the scheduling decisions can be taken independently of each other. The scheduler takes into account the channel conditions status labeled as channel quality inductor (CQI), which is updated regularly at each transmission time interval (TTI) [5]. The resource block is the basic

time-frequency unit in the scheduler, spanning 180 kHz in the frequency domain. The scheduler assigns resource blocks to a user each 1 ms of scheduling interval [6].

Several algorithms have been proposed such as round robin (RR), proportional fairness (PF), modified largest weighted delay first (M-LWDF), and exponential rule (EXP-rule) schemes to improve the resource allocation performance in terms of throughput and fairness.

The RR provides a fair time resource sharing among the users. However, in wireless systems, this approach is not fair in terms of user throughput, due to the fact that it does not depend solitarily on the amount of time in which the resources are occupied, but also on the experienced channel conditions. The introduction of PF solved that problem [7]. It considers both channel condition and average throughput to determine the transmission order among the users. The PF metric is obtained by merging blind equal throughput (BET) and maximum throughput (MT). BET aims at serving all users equally in terms of throughput, whereas MT prioritizes the users who have better channel conditions. Although PF strategy shows high performance for non-real time applications, it is inefficient for real time applications, because it does not consider delay requirements for real time applications. Moreover, as a guaranteed delay technique, M-LWDF is proposed in [8, 9]. It shows better performance than PF since it takes delay requirements into consideration. This scheduling guarantees packet delivery within the specific delay budget. The delay metric is used for shaping the behavior of PF; it even assures a good balance among spectral efficiency and fairness, but it is not concerned about the user's preferences. Furthermore, to increase the end-to-end system delay sensitivity, EXP/PF is proposed in [10] resulting in an improved performance. EXP/PF is based on the behavior shapes of the PF algorithm by taking an exponential function of the end-to-end system delay. Even though previous scheduling algorithms have succeeded to provide better performance of the real and non-real time applications, there is still a main drawback in the static way of decision making. In other words, it could not be adapted to changeable application's preferences with time.

A new concept for scheduling, such as game theory (bankruptcy and shapely value), was proposed to enable bandwidth sharing between coalitions of applications, resulting in an improvement in resource allocations [11]. Authors in [12] used cooperative game theory concept to allocate the resources over LTE technology. Furthermore, the Nash Bargaining Solution (NBS) concept is utilized to address the fairness issue by introducing an optimal fair resource allocation. Using the game theory concept, this scheme illustrates a high fairness level. The main drawback of the game theory is that a large number of users add further complexity to the system. To solve such a problem, the users are grouped into 2 users, rather than n -users group. In the same manner, the shapely value algorithm is proposed in [13] to perform the resource allocation for the real time services. It shows an improved performance and trade-off between the throughput gain and fairness index.

Recently, a new scheduling algorithm has been proposed for smart grid applications over LTE technology. Moreover,

this scheduler is based on the mathematical game theory concept to define linear optimization for the resource allocation problem. For that reason, an algorithm is derived and analyzed theoretically. This algorithm concludes that if the new algorithms are used to enhance the latency, LTE could be utilized to support smart grid applications [14–16]. In [17], cooperative game theory (bankruptcy and shapely value) is proposed with the modified EXP-rule and M-LWDF algorithms, by introducing virtual token mechanism. The proposed mechanism works by forming coalitions between flow classes to distribute the bandwidth fairly among all users and gives priority to real time flows. Even if this approach is suitable for real time applications, it is not concerned about non-real time applications.

However, this paper proposes a combination of game theory (bankruptcy and shapely value) and TOPSIS concepts for smart grid applications. This combination has significantly improved the scheduling scheme. In addition, the proposed novel scheme considers four criteria (delay, throughput, fairness, and queue length) for both real and non-real time applications. It is worth mentioning that the existing algorithms do not consider all these criteria at the same time for real and non-real time applications together. The use of game theory concept (bankruptcy and shapely value) provides a fair resource sharing between applications. To start with, bankruptcy forms a coalition between applications so that the distribution decision is shared among a group of applications rather than individual application. Consequently, bankruptcy algorithm utilizes transferable utility (TU) concept (bandwidth in our approach), which allows shifting the benefits among applications. For instant, if the number of application's users suddenly increases, more resources are assigned to this application (class) from other applications. Furthermore, the shapely value algorithm adds an essential enhancement to the scheduling mechanism where it distributes the resources fairly among the applications as a proportion, which prevents low priority classes from being starved. TOPSIS concept prioritizes the application's users based on their criteria and the application's preferences. The priority will be given to the users with urgent requirements (e.g., delay). To the best of our knowledge, the evaluation study of these three applications using the TOPSIS and the game theory combination is considered novel.

The rest of this paper is structured in the following order. The proposed model and the theoretical and the related equations for the proposed algorithm are described in Section 2. Section 3 describes the procedure used for the game theory calculations of three smart grid applications. The evaluation of the proposed approaches and the simulation results are presented in Section 4. Finally, the conclusion and some ideas for future work are described in Section 5.

2. Proposed Model

The three smart grid applications (voice, video surveillance, and metering data) are classified into three classes (A , B , and E , resp.). The model consists of two levels where, on the first level, bankruptcy algorithm divides the available

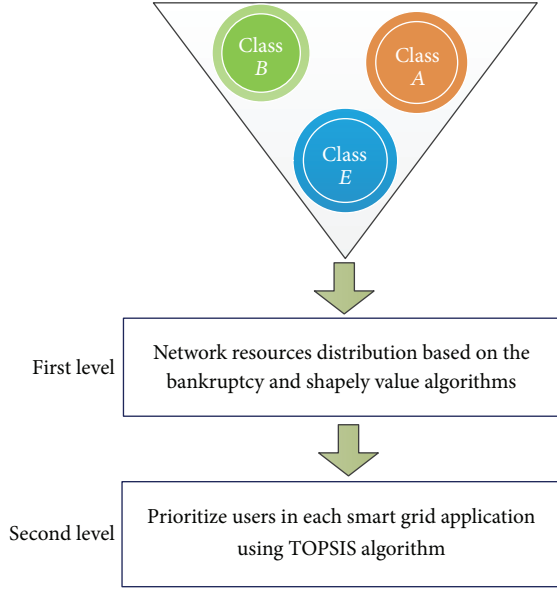


FIGURE 1: Main system diagram.

resources among a group of classes. Afterwards, shapely value fairly distributes the resources among classes as a proportion according to their demands, which results in serving the low priority classes without starvation.

On the second level, TOPSIS algorithm allocates the resources among the users of the class based on the class preferences. Figure 1 illustrates a general diagram of the proposed model.

2.1. Bankruptcy and Shapely Value. In order to divide the resources perfectly among the classes, bankruptcy forms a coalition between applications (classes), so that the distribution decision is shared among classes rather than individual users. To apply this mechanism, the transferable utility concept (bandwidth in our approach) is used to allow shifting the bandwidth among classes. For instance, if number of class A users suddenly increases, more resources are assigned to it from either class B or C. Bankruptcy determines the required data rate of classes based on the O'Neill approach [18], as shown in

$$U(S) = \max \left\{ C - \sum_{i \in N \setminus S} P_i \times K_i, 0 \right\}, \quad (1)$$

$$U(N) = C,$$

where $U(S)$ is the utility for the set of coalition S in the game, C is the total available system capacity, N is the set of the smart grid applications ($N = \{1, 2, \dots, n\}$), P_i is the required bandwidth for a smart grid application i , and K_i is the quantity of users in a smart grid application i .

Once all the potential coalitions among classes are calculated, shapely value distributes the resources fairly among them. The fairness distribution property of shapely value is based on the three main parameters (symmetry, additivity, and efficiency) [19, 20], where symmetry means there is no

relationship between the player's resource allocation and the order of the players entry into the game. Additivity axiom predicts the relationship between different values of the game and is valid for independent and composite games. The Pareto efficiency axiom guarantees that no player can earn a better allocation without worsening other players.

The shapely value concept prevents low priority classes from being starved since the resources are distributed as a proportion among classes, as shown in

$$\text{Sh}_i(U) = \sum_{S \subseteq N} W(S) \times (U(S) - U(S \setminus \{i\})) \quad (2)$$

$$\text{where } W(S) = \frac{(|S| - 1)! \times (n - |S|)!}{n!},$$

where $\text{Sh}_i(U)$ is the shapely value of smart grid application i (the worth of a smart grid application i in the game), $U(S \setminus \{i\})$ indicates the coalition utility S excluding the smart grid application i , n is the number of smart grid applications in the game, and $W(S)$ is the probability of entrance for smart grid applications to the game.

2.2. TOPSIS. TOPSIS method allows the scheduler to select the best option from all possible ones [21]. Furthermore, it is defined as a multiple-decision maker, which chooses the most appropriate solution from all potential alternatives. TOPSIS method has several advantages, such as multiple attribute decision making, guaranteed high satisfaction factor to the smart grid application preferences, low complexity, and robust scheduling decision. In this work, TOPSIS method is utilized to serve the smart grid application's users based on their criteria values and preferences. Moreover, four criteria are used to make the scheduling decision (delay, channel status, queue length, and the past average throughput). Such weighting coefficients increase the scheduling robustness, control, and dynamic adjustment. TOPSIS procedures are described in the following steps.

Step 1 (criteria value calculation). As the user criteria are the inputs of the TOPSIS algorithm, they are calculated as follows:

- (1) User m delay metric is the difference between the current time and the stamped time of the packet in the buffer queue, which is normalized by the delay budget of the related application

$$D_m(t) = \frac{t - T_{\text{stamp}m}}{d_i}, \quad (3)$$

where $D_m(t)$ is the delay factor of user m at time t , t is the real time, $T_{\text{stamp}m}$ is the entrance time of user m packets in the buffer queue, and d_i is the delay budget of application i .

- (2) The channel status metric of user m (CS_m) defines the channel quality in terms of the ability of data transmission. It is extracted from the signal to noise ratio, which is received by user m . It is updated periodically at each TTI for each user.

TABLE 1: TOPSIS evaluation criteria.

	Delay factor	Channel status	Queue length	Past average throughput
User 1	$D_1(t)$	$CS_1(t)$	$QL_1(t)$	$\overline{TH}_1(t)$
User 2	$D_2(t)$	$CS_2(t)$	$QL_2(t)$	$\overline{TH}_2(t)$
\vdots	\vdots	\vdots	\vdots	\vdots
User l	$D_l(t)$	$CS_l(t)$	$QL_l(t)$	$\overline{TH}_l(t)$

- (3) The queue length metric is used as a pointer to give the situation of the user's buffer, and it is calculated as follows:

$$QL_m(t) = \frac{Q_m(t)}{Q}, \quad (4)$$

where $QL_m(t)$ is the queue length metric of user m at time t , $Q_m(t)$ is the number of packets of user m in the buffer at time t , and Q is the total accommodation capacity of the buffer.

- (4) The past average throughput metric is used as a pointer to determine the data rate, which has been transmitted to user m in the previous TTI. It is calculated as a moving average, as shown in

$$\overline{TH}_m(t) = \alpha \cdot \overline{TH}_m(t-1) + (1-\alpha) \cdot r_m(t) \quad (5)$$

where $0 \leq \alpha \leq 1$,

where $\overline{TH}_m(t)$ is the past average throughput of user m , α is constant related to the window size, and $r_m(t)$ is the acquired data rate of user m at time t .

After calculating the evaluation criteria (Step 1, as above) for each user, they will be inserted into Table 1.

$$v(t) = \begin{bmatrix} w_D \times D_1(t) & w_{CS} \times CS_1(t) & w_{QL} \times QL_1(t) & w_{\overline{TH}} \times \overline{TH}_1(t) \\ w_D \times D_2(t) & w_{CS} \times CS_2(t) & w_{QL} \times QL_2(t) & w_{\overline{TH}} \times \overline{TH}_2(t) \\ \vdots & \vdots & \vdots & \vdots \\ w_D \times D_l(t) & w_{CS} \times CS_l(t) & w_{QL} \times QL_l(t) & w_{\overline{TH}} \times \overline{TH}_l(t) \end{bmatrix}, \quad (8)$$

where $v(t)$ is the decision matrix and w_D , w_{CS} , w_{QL} , and $w_{\overline{TH}}$ are the attribute weights for delay, channel status, queue length, and past average throughput, respectively.

Step 4 (separation measurement calculation based on the Euclidean distance). TOPSIS utilizes Euclidean distances to measure the separation measurement for users (positive ideal value and negative ideal value). The user, who is prioritized to serve, supposed to have the shortest distance from the positive ideal value and the farthest distance from the negative ideal value. The positive ideal value is calculated by

Step 2 (construct the normalized decision matrix). To make a decision over multicriteria using TOPSIS algorithm, each attribute is transferred from dimensions into dimensionless by finding the normalized value of criteria j related to user m as it is shown in (6). The matrix in (7) contains the normalized attribute values of all users. Consider

$$r_{mj} = \frac{x_{mj}}{\sqrt{\sum_{m=1}^l x_{mj}^2}}, \quad (6)$$

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1y} \\ r_{21} & r_{22} & \cdots & r_{2y} \\ \vdots & \vdots & \vdots & \vdots \\ r_{l1} & r_{l2} & \cdots & r_{ly} \end{bmatrix}, \quad (7)$$

where r_{mj} is the normalized value of user m metric j , x_{mj} is the value of user m metric j , and R is the normalized decision matrix.

Step 3 (construct the weighted normalized decision matrix). The weighted matrix is obtained by multiplying each attribute from the normalized decision matrix by its associated weight. As we mentioned earlier, each metric has specific weight, which is chosen carefully to be appropriate to the smart grid application demands. For instance, voice application requires higher concentration on the delay factor and queue length rather than past average throughput and channel status. Video surveillance application has a little more tolerance to delay with as much fewer packet loss rate (PLR) as possible. On the other hand, the metering data application requires the highest data rate, to achieve that the higher weights on channel status and past average throughput than other criteria will be given. It is worth mentioning that the sum of the criteria weights is equal to 100%.

Each of the criteria values is updated at each TTI, and the weight related to each criterion is multiplied by criteria values for each smart grid application, as illustrated in

the summation of the Euclidean distance between the user criteria values and the highest criteria values among all the users, as shown in

$$S_m^* = \sqrt{\sum_{j=1}^y (v_{mj}(t) - v_j^*(t))^2}, \quad m = (1, 2, \dots, y), \quad (9)$$

where S_m^* is the user m separation measurement from the ideal value at time t .

Similarly, the negative ideal value is calculated by the summation of the Euclidean distance between the user criteria values and the lowest criteria values among all the users, as shown in

$$S_m^- = \sqrt{\sum_{j=1}^y (v_{mj}(t) - v_j^-(t))^2}, \quad m = (1, 2, \dots, y), \quad (10)$$

where S_m^- is the user m separation measurement of negative ideal value at time t .

At the end of Step 4, two values, namely, S_m^* and S_m^- , for each metric have been counted. These two values represent the distance between each metric and both the ideal and the negative ideal metric values.

Step 5 (closeness to the ideal solution calculation). In the process, the closeness of user m to the ideal solution is defined as

$$C_m^*(t) = \frac{S_m^-(t)}{S_m^*(t) + S_m^-(t)}, \quad 0 < C_m^* < 1, \quad (m = 1, 2, \dots, l), \quad (11)$$

where $C_m^*(t)$ defines how much the user m is close to the ideal solution.

Step 6 (prioritize the users in each smart grid application). The set of the users can now be ranked according to the descending order of criteria where the highest value will be the first to be served, and so on.

3. Game Theory Calculations

Various applications require different data rates. In this scenario, voice, video surveillance, and metering data applications require 32, 242, and 500 kbps, respectively [22]. The bandwidth is assumed to be 15 MHz, which corresponds to 75 RBs, and the system's capacity is 54 Mbps [23].

On the first level, the characteristic functions for probabilities of all potential coalitions among classes are calculated as follows:

$$\begin{aligned} U(A) &= \max \{54000 - (242 \times K_B + 500 \times K_E), 0\}, \\ U(B) &= \max \{54000 - (32 \times K_A + 500 \times K_E), 0\}, \\ U(E) &= \max \{54000 - (32 \times K_A + 242 \times K_B), 0\}, \\ U(A, B) &= \max \{54000 - (500 \times K_E), 0\}, \\ U(A, E) &= \max \{54000 - (242 \times K_B), 0\}, \\ U(B, E) &= \max \{54000 - (32 \times K_A), 0\}, \\ U(A, B, E) &= 54000, \end{aligned} \quad (12)$$

where $U(A)$, $U(B)$, and $U(E)$ are the utility of voice, video surveillance, and metering data, respectively, and K_A , K_B , and K_E are the flow quantity of voice, video surveillance, and metering data, respectively.

TABLE 2: With and without bankruptcy and shapely value calculations.

Bankruptcy value (kbps)	Characteristic function	Without coalition (kbps)	Shapley value calculation (kbps)
40000	{A}	1280	13653.3333
48520	{B}	9000	22173.3333
44520	{E}	5000	18173.3333
49000	{A, B}		
45000	{A, E}		
53520	{B, E}		
54000	{A, B, E}		

Assume 80 users are assigned to the voice, video surveillance, and metering data applications (40, 30, and 10, resp.). Bankruptcy and shapely values are calculated, as shown in Table 2.

As can be seen from Table 2, the use of coalition concept will increase the bandwidth efficiency roughly up to 10, 2, and 3 times (voice, video, and metering data).

On the second level, TOPSIS prioritizes the class's users for scheduling based on their criteria values and weighting coefficients. It is worth mentioning that these weights were experimentally selected because they showed a good performance. This experiment is inspired by trial-based technique which is based on considering different weight values and then simulates them. Consequently, after testing the upper and lower values from the experimental value, we ensure that the proper selection is done.

4. Results and Discussion

The simulation was conducted using LTE-Simulink built on C++ platform. One cell is considered in this scenario which includes noise and interferences. The propagation model such as simple path loss is based on the distance from the base station and multipath losses are used. Furthermore, shadowing based on log normal distribution (0 dB and 8 dB) and penetration loss with 12 dB is used. The fairness among each user is measured using Jain's fairness method [24].

The proposed algorithm is conducted under two scenarios. The first scenario is dedicated to voice and video (real time applications) whereas the second scenario considers all applications including (real time and non-real time applications). The purpose of the two scenarios is to demonstrate the robustness of the proposed algorithm.

Figure 2 shows the comparison of the proposed algorithm with PF, EXP/PF, and M-LWDF for the first scenario. The proposed algorithm shows the best performance in the overloaded situation by roughly 16% compared to the other algorithms. EXP/PF and M-LWDF show better performance (30 to 50 users) than PF, which shows the worst performance since it does not consider the delay factor. Figure 3 illustrates that the proposed scheme shows the lowest delay compared to other schemes.

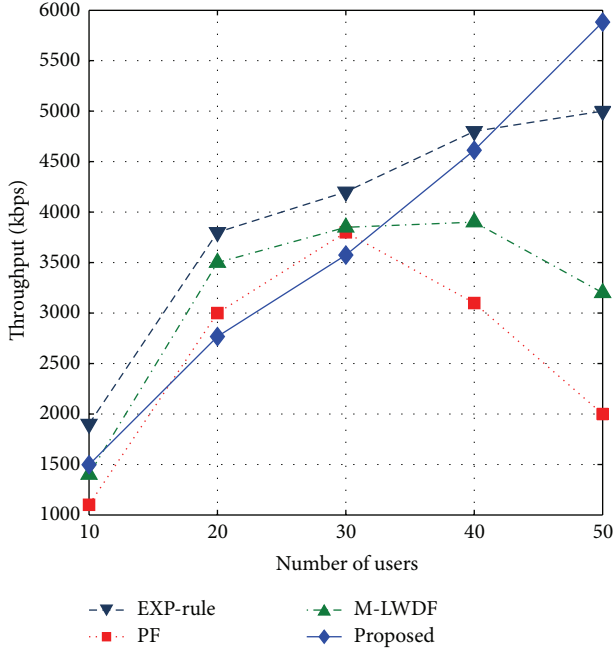


FIGURE 2: Aggregate throughput of voice and video applications.

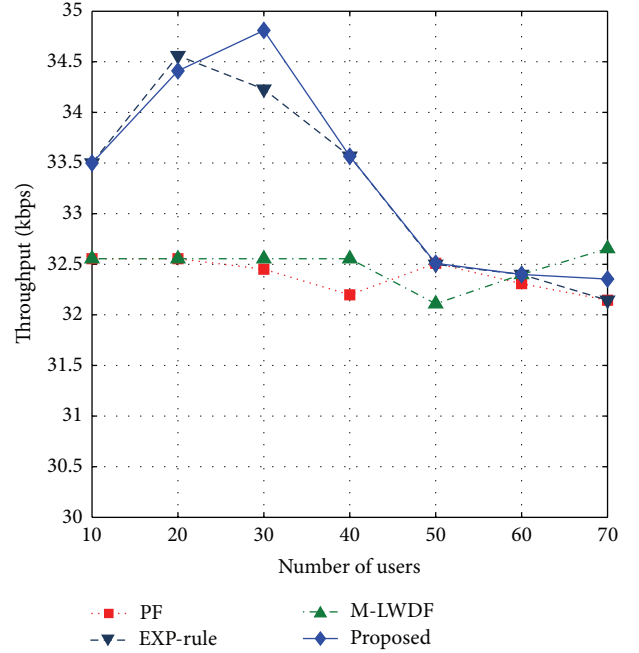


FIGURE 4: Average throughput of voice application.

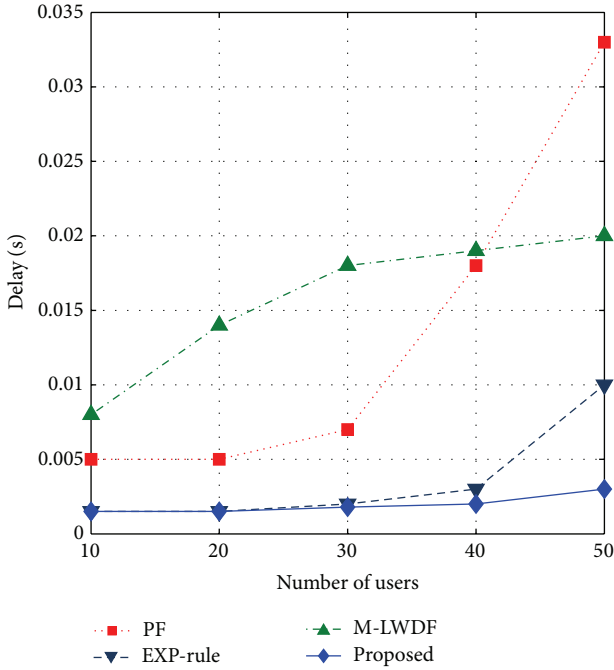


FIGURE 3: Delay of voice and video applications.

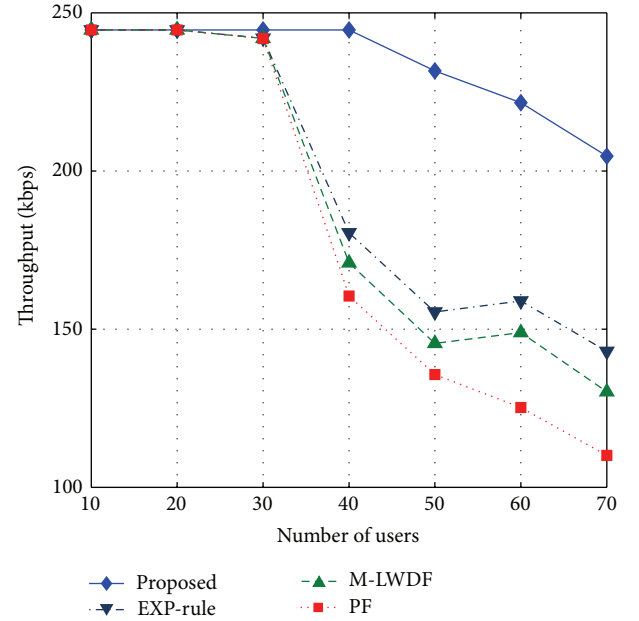


FIGURE 5: Average throughput for video surveillance application.

In the second scenario, all schemes show a good performance for the minimum data rate requirements (32 kbps) of the satisfied voice application, as shown in Figure 4. Furthermore, referring to Figure 5, all the scheduling schemes met the video surveillance traffic requirements up to 30 users, but they dropped significantly (more than 30 users) except the proposed algorithm, which kept serving the video traffic up to 42 users (overloaded situation). In fact, the reason behind

robustness of the proposed algorithm is the dynamic adjustment to smart grid application's requirements. PF showed the worst performance for video surveillance application since it is not concerned about the delay factor and it has been designed to serve non-real time applications. The average throughput for metering data flows is illustrated in Figure 6 where the proposed algorithm shows a good improvement, approximately 15% higher than the other algorithms (up to 60 users). Moreover, PF shows a good performance in

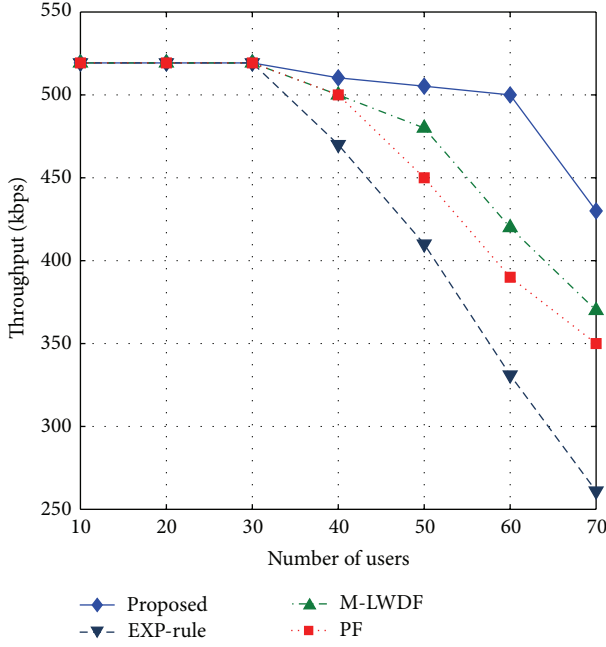


FIGURE 6: Average throughput for metering data application.

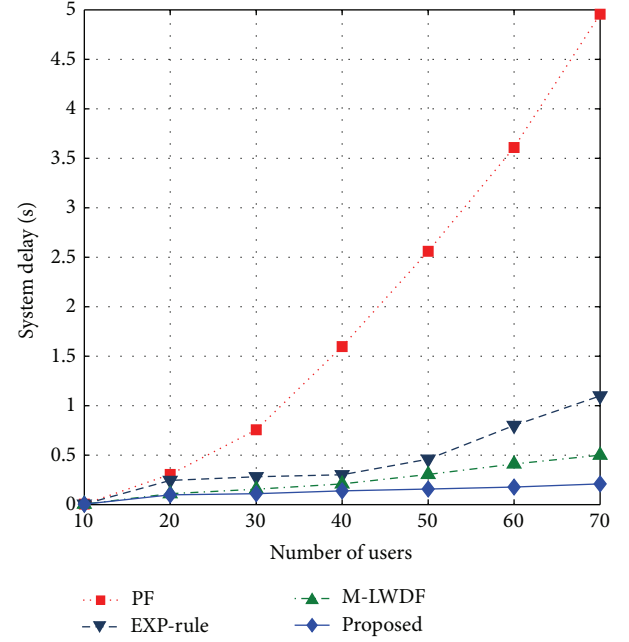


FIGURE 8: Average system delay.

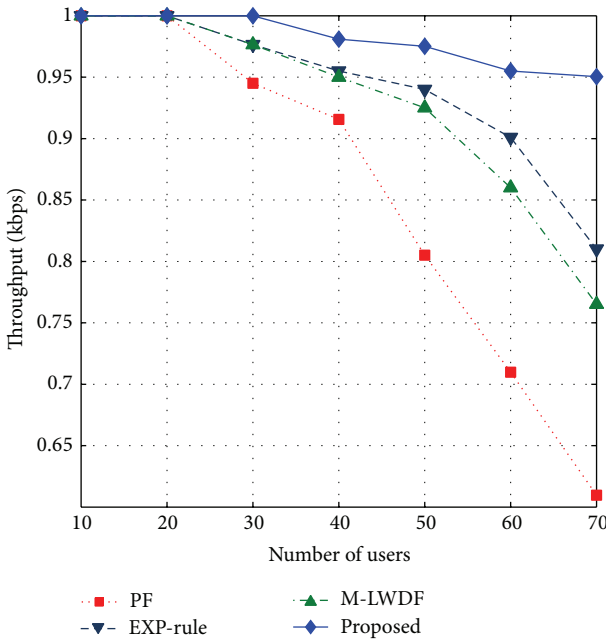


FIGURE 7: Average system fair index.

an overloaded situation since its metric is designed to serve users with high data rate and allow high tolerance in terms of delay, whereas EXP-rule shows the worst performance since it considers the end-to-end system delay regardless bandwidth requirements.

The proposed algorithm shows the highest fairness and lowest delay compared to the other schemes (Figures 7 and 8), in view of the fact that the proposed algorithm assigns higher weights to delay factors for real time applications, as

mentioned earlier. In addition, all users (real and non-real time users) had a chance to be served (no starvation for non-real time applications). In contrast, PF shows the lowest fairness index and the highest delay since it is not concerned about the delay metric at all, and the probability of packet drop rate increases along with the number of users increases. As a result, PF failed to cover more than 30 users with respect to the traffics delay boundaries.

5. Conclusion

This paper has presented a new scheduling scheme composed of game theory (bankruptcy and shapely value) and TOPSIS mechanisms in LTE network. The proposed algorithm was implemented in three smart grid applications, namely, voice, video surveillance, and metering data. In the real time scenario, the proposed algorithm shows the best performance in terms of delay and throughput, since it distributes the resource perfectly and takes into account delay and queue length. In terms of voice applications, all other schemes (PF, EXP/PF, and M-LWDF) satisfied the minimum requirements (32 kbps) in an overloaded situation (up to 70 users), whereas the proposed algorithm showed even better performance reaching up to 35 kbps. In terms of video and metering data, the proposed algorithm also demonstrated higher performance than the other algorithms by serving up to 42 users for video application and 60 users for the metering data application. Finally, this novel algorithm showed the lowest delay and the highest fairness of approximately 0.98. The authors believe that this novel algorithm can be applied to other real time and non-real time applications, and it can be extended beyond LTE to serve LTE advanced applications.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgments

This research work is supported by the Science Fund Grant (Grant no. SF002-2014) and University of Malaya Research Grant (UMRG) scheme (RG286-14AFR).

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